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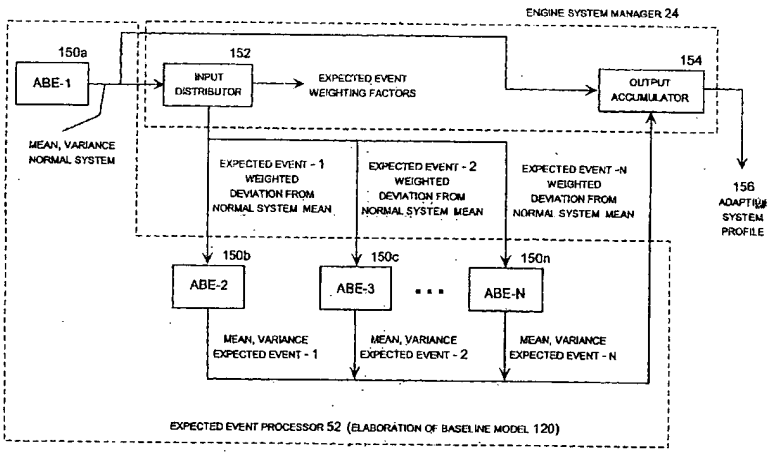
(54) Title: COMPUTER PERFORMANCE ESTIMATION SYSTEM CONFIGURED TO TAKE EXPECTED EVENTS INTO CONSIDERATION



(57) Abstract: The present invention may be embodied as expected event scheduler and processor in an application performance monitoring (APM) services. The expected event scheduler and processor allows the APM system to take scheduled events into account when performing the performance forecasting for the host system. The learned parameters may be based on measured input values including internal measurements, such as data from monitoring agents located within the host computer system, as well as external measurements relating to factors such as computer backup runs, monthly payroll runs, quarterly financial reporting runs, weekends, holidays, weather data, traffic data, advertisements run by the operator of the system or others, promotional events, product releases, news announcements, elections and other natural and demographic factors. The expected events may overlap in time, and the expected event scheduler and processor learns weighing factors for the simultaneously occurring expected events by updating the learned parameters over successive time trials.

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COMPUTER PERFORMANCE ESTIMATION SYSTEM CONFIGURED TO TAKE EXPECTED EVENTS INTO CONSIDERATION

REFERENCED TO RELATED APPLICATIONS

This application claims priority to commonly-owned U.S. Provisional Patent Application Serial. No. 60/514,701 filed on October 27, 2003. This application incorporates by reference the disclosures of the following commonly-owned patents and patent applications: U.S. Patent No. 5,835,902; U.S. Patent No. 6,216,119; U.S. Patent No. 6,289,330; U.S. Patent No._____ (allowed U.S. Patent Application Serial No. 09/811,163); U.S. Patent No._____ (pending U.S. Patent Application Serial No. 10/165,232, and U.S. Patent No._____(pending U.S. Patent Application Serial No.10/324,641).

TECHNICAL FIELD

This invention relates to a computerized estimation system and, more specifically, relates to a computerized estimation system that takes expected events into account in the estimation. In particular, the disclosed embodiment may be implemented as an computer performance estimation system providing application performance monitoring (APM) services that takes scheduled and seasonal events into account in the computer performance estimation.

BACKGROUND OF THE INVENTION

A variety of sophisticated systems have been developed for monitoring and forecasting performance in various fields. These monitoring and forecasting systems may be referred to, collectively or individually, as "estimation systems." For example, conventional statistics systems, artificial neural network systems, or concurrent learning and information processing (CLIP) systems capable of monitoring and forecasting a large number of variables have been developed for use in a variety of fields including computer performance monitoring and forecasting, visual image processing, electricity demand forecasting, and commodity price forecasting. These estimation systems typically use a number of measured input values to impute (i.e., estimate for a current time trial) current values for monitoring, and they may also predict (i.e., estimate for future time trials) future input values. In particular, these systems may compare imputed input

values with actual input values to identify abnormal input values when they occur, and they may also predict or forecast the likelihood that future input values will become abnormal.

The mathematical core technology of these monitoring and forecasting systems may involve the computation of a matrix of estimation parameters, also called learned parameters. This matrix typically contains observed relationships, such as the covariances, between input and output variables. Estimation systems may also utilize the inverse of the covariance matrix, which is sometimes referred to as a "connection weight matrix." In particular, the elements of the covariance matrix are typically estimated through the application of statistical analysis to a historical database of input and output values. Once the covariance matrix has been computed, it may be inverted to obtain the connection weight matrix, which can be used to directly compute estimates for the output values from a given set of input values through standard matrix computations.

Moreover, once the covariance and connection weight matrices have been initially determined, they may be used to perform monitoring and forecasting on a CLIP basis. That is, a new set of computed output values may be computed for each time trial of measured input values, and for each time trial either the covariance matrix, the connection weight matrix, or both may be updated to achieve learning while the system performs its monitoring and prediction functions. See in particular U.S Patent No. 5,835,902.

In connection with using these types of estimation systems for time-based parameters, such as computer performance, expected events are typically superimposed on top of the "normal" system performance without these factors. For example, seasonal holiday events cause an expected deviation from the normal system performance. In addition, scheduled events such as payroll processing quarterly report processing, and system backup operations can also cause an expected deviation from the normal system performance.

Unfortunately, these expected events can cause false alarms in by the computer performance monitoring system. Given the type of events under consideration, staff technicians may often be off work, for example during holidays or scheduled processing performed outside of regular business hours. Such false alarms can therefore be most inconvenient. One approach to addressing this problem is to suspend the computer performance monitoring during these

expected events. However, this practice runs the risk of missing a real system problem, which might be exacerbated by the absence of staff technicians.

Moreover, expected events can overlap in time, which can increase the likelihood of false alarms during these periods. Therefore, a continuing need exists for effective and efficient methods and systems for handling expected events, such as seasonal and scheduled events, in estimation systems. A particular need exists for these methods and systems for computer performance estimation systems.

SUMMARY OF THE INVENTION

The present invention meets the needs described above in a computerized estimation system that takes expected events into account in the estimation. In particular, the disclosed embodiment may be implemented as an computer performance estimation system providing application performance monitoring (APM) services that takes scheduled and seasonal events into account in the computer performance estimation. In an AMP system, for example, expected event scheduler and processor takes expected events into account when monitoring and forecasting the performance of the host computer system. The learned parameters may be based on measured input values including internal measurements, such as data from monitoring agents located within the host computer system of the host computer system. The learned parameters may also be based on external measurements relating to factors such as computer backup runs, monthly payroll runs, quarterly financial reporting runs, weekends, holidays, weather data, traffic data, advertisements run by the operator of the system or others, other promotional activities or events, product releases, news announcements, elections and other natural and demographic factors. The expected events may overlap in time, and the expected event scheduler and processor learn weighing factor for the simultaneously occurring expected events through updating applied to the learned parameters over successive time trials.

In this manner, the invention improves the accuracy of the estimation system, typically a monitoring and forecasting system, and avoids false alarms attributable to expected events that can be, and should be, taken into account. In addition, the present event avoids such false alarms without suspending the computer performance monitoring during these expected events, which would disadvantageously run the risk of missing a real system problem. As noted above,

this situation might be exacerbated by the absence of staff technicians in the absence of the present invention.

Generally described, the present invention may be embodied as an expected event scheduler and processor system in or for an estimation system for a host system operable for receiving input values for successive time trials and, for each time trial, computing output values based on the input values and learned parameters and updating the learned parameters to reflect relationships observed among the input and output values The method for implementing the expected event system includes identifying expected events and provisioning the estimation system with learned parameters for the expected events. The learned parameters for the expected events are then initialized, the estimation system is run during successive time trail to forecast operation of the host system as effected by the expected events while updating the learned parameters including the learned parameters for the expected events.

Running the estimation system includes receiving measured data corresponding to operation of the host system for a current time trial and estimating operation of the host system for the current time trial using imputed learned parameters. Running the estimation system also includes predicting operation of the host system for future time trial using forecasted learned parameters and updating the learned parameters based on the measured data received for the current time trial. The estimation system then repeating these steps for a number of successive time trials.

The expected events typically include scheduled events and seasonal events. The expected events may also include multiple overlapping expected events. In this case, the learned parameters include weighting factors for the overlapping expected event. In addition, the estimation system may monitor and forecast the performance of the computer system that includes a computer network including application servers, storage servers, routers, and interconnecting data transmission lines. For this type of estimation system, the expected events may include end-of-month processing events, end-of-quarter processing events, and scheduled backup events. The expected event may also include weekends and holidays.

The measured data typically includes internally-generated factor, such as data received from one or more monitoring agents deployed within the computer system. The measured data may also include data received from one or more sources external to the computer system.

In addition, the invention may be implemented as a method implemented by computer hardware, or as a computer storage medium storing executable instructions for causing a computer system to implement the method.

In view of the foregoing, it will be appreciated that the present invention greatly improves the operation of computer performance estimation systems in the presence of expected events, such as scheduled and seasonal events. The specific techniques and structures employed by the invention to improve over the drawbacks of prior estimation systems to accomplish the advantages described above will become apparent from the following detailed description of the embodiments of the invention and the appended drawings and claims.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. 1 is a block diagram of a multi-kernel concurrent learning and information processing (CLIP) system that supports the computer performance estimation system configured to take expected events into consideration of the present invention.

FIG. 2 is a block diagram of a computer performance estimation system implemented within the CLIP system of FIG. 1.

FIG. 3 is a block diagram of a baseline system implemented within the computer performance estimation system of FIG. 4.

FIG. 4 is a block diagram of baseline system of FIG. 3 configured to take expected events into account.

FIG. 5 is a logic flow diagram illustrating a routine for operating an expected event processor.

FIG. 6 is a graph illustrating computer performance with an expected event superimposed on the normal system behavior.

FIG. 7 is a graph illustrating the normal system behavior within the combined profile of FIG. 6.

FIG. 8 is the graph of FIG. 6 illustrating the normal system behavior and the additional profile associated with the expected event.

FIG. 9 is a graph illustrating computer performance with two expected events superimposed on the normal system behavior.

DETAILED DESCRIPTION OF THE EMBODIMENTS

The present invention may be embodied as expected event scheduler and processor in or for estimation systems generally and, in particular, computer performance estimation systems such as those performing application performance monitoring (APM) services. The expected event scheduler and processor allows the estimation system to take scheduled events into account when performing the estimation for the host system. In an AMP system, for example, expected event scheduler and processor takes expected events into account when monitoring and forecasting the performance of the host computer system. The learned parameters may be based on measured input values including internal measurements, such as data from monitoring agents located within the host computer system of the host computer system. The learned parameters may also be based on external measurements relating to factors such as computer backup runs, monthly payroll runs, quarterly financial reporting runs, weekends, holidays, weather data, traffic data, advertisements run by the operator of the system or others, other promotional activities or events, product releases, news announcements, elections and other natural and demographic factors. The expected events may overlap in time, and the expected event scheduler and processor learn weighing factor for the simultaneously occurring expected events through updating applied to the learned parameters over successive time trials.

In particular, the present invention may, but need not necessarily, be embodied in an estimation system that utilizes learned parameters including a matrix containing covariance values between input and output variables or the inverse of the covariance matrix, which is also called a connection weight matrix. In a concurrent learning and information processing (CLIP) system, the values of the connection weight matrix are typically determined through the application of correlation analysis to a historical database of input and output values. The learned parameters are then updated over successive time trials as the CLIP system also monitors and forecasts the output values selected for the host system.

More specifically, once the covariance and connection weight matrices have been initially determined, they may be used to perform monitoring and forecasting

of a variety of system on a real-time basis. That is, a new set of output values may be computed for each time trial of measured input values. In addition, the connection weight matrix may be updated for each time trial to implement learning while the system performs its monitoring and prediction functions. In an AMP system, for example, the CLIP system updates the learned parameters while monitoring and forecasting the performance of the host computer system over successive time trials. The updating of the connection weight matrix can be performed in two ways. First, the covariance matrix may be updated for each time trial and then inverted. Second, the inverted covariance matrix may be updated directly. The basic single-kernel CLIP system and a number of its applications are described in commonly-owned U.S. Patent No. 5,835,902. A multi multi-kernel CLIP system and a number of its applications are described in U.S. Patent Nos. 6,216,119 and 6,289,330.

FIG. 1 is a functional block diagram of a multi-kernel CLIP monitoring and forecasting engine system **10** that has been augmented to take multiple expected events into consideration when monitoring and forecasting its objective parameters, such as those used to monitoring and forecast the performance of a computer system. As noted above, the engine system **10** may comprise one or more kernel units **18**, each of which may operate according to its own configuration parameters.

U.S. Patent Application Serial No. 10/165,232 describes refinement operations for the engine system **10** including continual evaluation of a set of competing statistical models based on differing configuration parameters, through which the kernel units **18** may operate simultaneously and competitively on-line, with output being tied to only one of them. For example, the recent performance of several kernels monitoring and forecasting the objective parameters for the host system may be compared off-line by the manager **24**, and the best performing kernel unit **18** is then selected for use until the next time the performance of the several kernels is compared off-line. The engine system **10** may implement these refinement operations, as governed by the engine system manager **24**, in two distinct modes, an on-line mode and an off-line mode.

In the on-line mode, the engine system **10** produces estimates and updates learned system parameters continually over consecutive time trails based on a fixed set of configuration parameters **10**. By contrast, in the off-line mode the

estimation system operates so as to change the configuration parameters **10** without either producing estimates or updating learned parameters. Moreover, in the on-line mode the estimation system **10** operates quickly and for the most part recursively to produce estimates and update learning during each time trial. By contrast, in the off-line mode the engine system **10** typically performs refinement operations relatively slowly and for the most part iteratively, through operations that either interrupt on-line operations or operate separately but at the same time. In both modes, however, the engine system **10** typically operates automatically. In the off-line mode, the engine system **10** performs refinement operations as governed by the manager **24**. Refinement operations first assess the quality of the current configuration parameters, after which they modify the configuration parameters, as appropriate.

This patent application also describes a semi-automated analysis process that functions to refine the kernels in a way that allows analysts to analyze historical datasets in order to determine a desired set of configuration parameters for those datasets. As part of this semi-automated process, the refinement processor may implement refinement operations including removing redundant measurement features, removing unnecessary measurement features, identifying optimal learning weights, and identifying beneficial uses of recent trends. As noted above, this application further specifies a fully automated analyzer that, unlike its semi-automated counterpart, requires neither historical data nor manual operation. Instead, the fully automated analyzer routinely compares competing models, identifies the model that performs best according to selected criteria, and replaces the currently operating model with the best performing model in accordance with a selected schedule in fully automatic fashion.

The engine system **10** typically operates in the on-line mode by receiving input values **12** via the transducer **16** at the beginning of every fifteen minute time trial. Next, during the same fifteen minute time trial, the engine system **10** performs two additional operations, delivering output values **14** via the transducer **16** and updating learned parameter values associated with one or more kernel units **18**. Taken together, kernel units **18** specifications and transducer **16** specifications constitute definitions of one or more estimation models that the engine system **10** utilizes during on-line operation. The engine system **10** may also occasionally receive, via the kernel units **18**, a set of updated configuration

parameters **26**, which may in turn signal the need of modifications in the operation of the kernel units **18** and the transducer **16**, in which case the manager **24** may initiate off-line refinement operations as described above. In particular, these refinement operations typically modify the configuration parameters **26** in such a way that the kernel units **18** will correct for input values **12** and transducer **16** values that are linearly redundant or otherwise ineffective as monitoring or forecasting parameters.

In addition, the engine system **10** may operate as a dynamically linked library (DLL), which is linked to an executable computer program (EXE) via an application-program interface (API). In terms of the labeled components in FIG. 1, during on-line operation the input values **12** are sent by the EXE to the engine system **10** via the API, and output values **14** are sent back to the EXE by the engine system **10** via the API. During engine system **10** initialization, the EXE also supplies initial configuration parameters via the API. After initialization, some of these initial configuration parameters may change as part of the automatic estimation system refinement process, while others may not.

U.S. Application Serial No. 09/811,163 describes a CLIP-based computer system performance estimation system **30** (also referred to as an application performance monitoring or "APM" system). In this APM system, the learned parameters may be based measured input values including internally-generated measurements, such as data from monitoring agents located within the host computer system. The learned parameters may be based on measured input values including external measurements relating to factors such as weather data, traffic data, advertisements run by the operator of the system or others, other promotional activities or events, product releases, news announcements, elections and other natural and demographic factors. In fact, the basic CLIP-based APM system can learn correlations that may exist between the behavior of the host computer system based on any parameter for which data can be gathered. Those measured parameters that are effective in predicting the behavior of the host computer system (i.e., have a significant non-zero correlation over time) are retained as predictive parameters and those that do not are eliminated from the model.

U.S. Application Serial No. 10/324,641 describes improvements to the APM system **30** including a baseline system **26** and an alarm service **40** for computer

networks and server systems exhibiting erratic motions that contain repeating characteristics, such as global trends, cyclical variations, and seasonal variations. The baseline model **26** learns these behaviors by capturing the signatures of input variables measured for the monitored system and adapting the signatures over time, improving their accuracy, and automatically learning changes in behavior as they occur. Because the baseline model **26** captures the signatures based on an analysis of received data over successive time trial, it bypasses the typical modeling stage of the commonly used methods of analysis. That is, the baseline system **26** captures and continually updates the monitored system's signatures, and uses these captured signatures to model the system, rather than relying on deterministic curve fitting or other classical types of data analysis, such as time series analysis and statistical analysis.

FIGS. 1 and 2 illustrate how the expected event scheduler **50** and the expected event processor **52** of the present invention tie into the engine system **10** and the computer performance estimation system **30** described above. The expected event scheduler **50** allows the user to specify expected seasonal and scheduled events, such as computer backup runs, monthly payroll runs, quarterly financial reporting runs, weekends, holidays and so forth. Internal and external measured data correlating with the computer performance during these events is included in the input values **12** shown in FIG. 1. As noted previously, learned parameters may be based measured input values **12** including internally-generated measurements, such as data from monitoring agents located within the host computer system. The learned parameters may also or alternatively be based on measured input values including external measurements, such as weather data, traffic data, advertisements run by the operator of the data from monitoring agents located within the host computer system of the host computer system, promotional activities, product releases, news announcements, elections and other natural and demographic factors. These input values are also used to learn parameters for normal computer system operation. But some input values may be included because they are correlated with normal computer system operation, while other input values may be included because they are correlated with computer system operation during expected events.

In any of these configurations, the engine system **10** is first provisioned for expected event consideration by configuring the kernel **18** and possibly the input

transducer **16** with learned parameters for these events including weighting factors for expected events scheduled to overlap in time. The expected event scheduler **50** is then configured with the schedules (i.e., the time periods when occurring) for the expected events. The engine system **10** is then run for successive time trials to compute predicted computer system behavior during normal periods and during expected events, which may overlap in time. The functionality for handling this situation is described in more detail below with reference to the expected event processor **52**.

Referring to FIG. 3, the baseline system **26** typically includes an adaptive baseline model (ABE) **120** and an adaptive correlation engine (ACE) **130**. The ABE and the ACE interface with the alarm service **40**, which typically includes a real-time alert detector **142**, a forecast alert detector **144**, and an alarm generator **146**. The ABE **120** and the ACE **130** (which consists of the transducer **16** and the multi-kernels **18a-n** in FIG. 1) also work in conjunction with the engine system manager **24**, which functions as a coordinator for the other system elements and manages the overall system activity during the running operation of the engine system **10**. Although these components are typically deployed as separate computer objects, they may be further subdivided or combined with each other or other objects in any manner suitable for a particular application. In addition, any of the components may be deployed locally or remotely, and may be combined with other functions and services.

During the running operation of the engine system **10**, the ABE **120** receives a set of measurements defining input variables for each time trial in a continually recurring set of time trials, which is represented by the input variable Y(t). Although the input variables typically include a vector containing multiple measurements, each input variable may be handled in the same manner. Therefore, for descriptive convenience, the methodology of the monitoring system is described for the representative input variable Y(t), which is also referred to as the "subject input variable," to distinguish it from the other input variables. However, it should be understood that this same methodology applies to all of the input variables in a multi-variable vector represented by Y(t).

That is, each input of several input variables is treated as the "subject input variable" for its own processing, and all of these input variables are processed for each time trial, typically simultaneously, although they could be processed

sequentially in some order. For this reason, the methodology is described below as applicable to a single "subject input variable" Y(t), and it is to be understood that multiple input variables are typically processed in a similar manner, either simultaneously or in some order. In addition, the ABE **120** may also receive additional input variables that are not processed as signatures, such as status indicators and configuration parameters.. However, these variables may be ignored for the purpose of describing the inventive aspects of the expected event scheduler **50** and processor **52**.

The operation of the ABE **120** is typically repeated for each time trial in a continual time series of time trials. In general, the ABE **120** continually receives measurement for the representative input variable Y(t), to define a time-based signature of measured values for that variable. In this time-based series, the time units are referred to as the "time index," which typically begins with time index "t=1" and sequentially run through "n" successive time trials for a repeating cycle. To permit estimation of the performance of the host computer system, the ABE **120** maintains a time-based baseline model for the representative input variable Y(t). More specifically, the ABE **120** defines a repeating cycle for the input variable Y(t) and computes a time-based mean and variance for each time period or "time slice" of the cycle. In other words, the ABE **120** defines a time-based baseline model for the input variable Y(t) that includes a time-based baseline mean and variance for each time index in the cycle. The cycle is typically defined by a user input parameter specifying a number of time slices "n" in the cycle. This parameter together with the inherent frequency of the input variable Y(t) defines a repeating cycle, which is typically the same for all of the input variables.

Further, the time-based baseline model for the input variable Y(t) is typically composed from a number of components, which the ABE **120** tracks individually. In particular, the signature for the input variable Y(t) may typically be decomposed into a global trend component G(t), a cyclical component C(t), a seasonal or scheduled component S(t), and an erratic component e(t), as reflected in a decomposition equation [i.e., $Y(t) = G(t) + C(t) + S(t) + e(t)$]. Nevertheless, it should be understood that these particular components are merely illustrative, and that the ABE **120** may track additional components, different components, only a subset of these components, as may be appropriate for a particular application. However, the illustrated set of components included in the decomposition equation described

above have been found to be well suited to a monitoring system for a complex computer network or server system.

Referring to FIG. 4, the expected event processor **52** may be implemented as an elaboration of the baseline system **26** shown on FIGS. 1 and 4. Even more specifically, the expected event processor **52** may be implemented as an elaboration of the baseline model or ABE **120** shown in FIG. 3 utilizing several simultaneous instantiations of the ABE, which are identified as ABE **150a-n** on FIG. 4. The expected event processor **52** provides a method and system for computing the value seasonal or scheduled component S(t) in the baseline composition equation [i.e., Y(t) = G(t) + C(t) + S(t) + e(t)] while taking expected events that may overlap in time into account in the manner described below.

The ABE-1 **150a** receives the input variables for each time trial and computes the expected means and variances of the learned parameters for normal system operation, as described in U.S. Application Serial No. 10/324,641. The input values, means and variances of the learned parameters for normal system operation are then passed to an input distributor **152** that computes, and learns through successive time trials, weighting factors for multiple expected events for each time trail. The input distributor **152** also computes the deviation of the measured input values and the expected means for these input values during normal system operation, as computed by the ABE-1 **150a**. The input distributor **152** then weights each deviation by its associated weighting factor. Each weighted deviation is then passed to an associated instantiation of the ABE **150b-n** as shown on FIG. 4.

The computation of the weight for a given ABE **150i** at the given time trial is typically achieved by taking the ratio of the variance computed by the given ABE **150i** at the given time trial to the sum of the variance of all overlapping expected events ABE **150a-n** at the given time trial.

Each individual ABE instantiation then compute the mean and variance for its associated expected event. That is, the ABE **150b** computes the mean and variance for the first expected event-1, the ABE **150c** computes the mean and variance for the second expected event-2, and so forth up to the ABE **150n**, which computes the mean and variance for the "Nth" expected event-N. The means and variances for the expected events are then passed to an output accumulator **154**,

which sums the expected event means and variances with the normal system mean and variance to product the complete adaptive system profile **156**.

FIG. 5 is a logic flow diagram illustrating a routine for operating the expected event scheduler **50** and the expected event processor **52**. In step **502**, the a technician configuring the engine system **10** identifies expected events and provisions the expected event schedule **50** with the time periods during which one or more expected events are scheduled. Step **502** is followed by step **504**, in which the engine system **10** including the kernel **18**, possibly the input transducer **16**, and the expected event processor **52** are provisioned to consider the expected events during the estimation of the host system operation. Specifically, the kernel **18** is provisioned with learned parameters for the expected event weighting factors and any additional input variables that are defined in association with the expected event processor. The input transducer **16** may be configured to weigh, combine or otherwise manipulate the raw input variables **12** into process variables for the kernel **18**. In addition, the expected event processor **52** is implemented including the input distributor **152**, the output accumulator **154**, and the capability to deploy multiple instantiations of the ABE **150a-n**. Step **504** is followed by step **506**, in which the learned parameters including the expected event weighting factors are assigned initial values based on heuristic estimation, off-line evaluation of historical data, or by running historical data through the estimation system once the expected event processor **52** has been provisioned.

Step **506** is followed by step **508**, in which the engine system **10** including the expected event processor **52** is run with real-time with data for successive time trials. Specifically, the engine system **10** forecasts and updates the learned parameters, including the weighting factors for the expected events, as it provides real-time monitoring and forecasting of the performance of the host computer system while taking the expected events into consideration. The engine system **10** also displays the system results and alarm status in the user interface **22**, such as the dashboard user interface **34** described in U.S. Application Ser. No. 09/811,163. The engine system **10** also operates the alarm service **40** as described in U.S. Application Ser. No. 10/324,641.

More specifically, as described in U.S. Patent Nos. 5,835,902; 6,216,119; and 6,289,330, and with reference to FIG. 1, step **508** typically includes step **510**,

in which the engine system **10** receives measured input data **12**, such as computer performance data for a time trial, which may be manipulated by the input transducer **16**. Step **510** is followed by step **512**, in which the engine system **10** estimates the computer system performance with imputed learned parameters, including imputed learned parameters associated with the weighting factors for the expected events, for the current time trial. Step **512** is followed by step **514**, in which the engine system **10** estimates the computer system performance with forecasted learned parameters, including forecasted learned parameters associated with the weighting factors for the expected events, for future time trials. Step **514** is followed by step **516**, in which the learned parameters are updated to reflect learning from the data received during the current time trial. Routine **500** then loops through steps **510** through **516** for each successive time trial as long as the engine system **10** continues to run for real-time data.

FIG. 6 is a graph showing a simplified representation of an illustrative computer performance **600** with an expected event superimposed on the normal system behavior. FIG. 7 is is a modified version of the graph shown in FIG. 6 showing the normal system behavior **602** within the computer performance **600**. FIG. 8 is a modified version of the graph shown in FIG. 7 illustrating the normal system behavior **602** and the additional profile associated with the expected event **604** within the computer performance **600**. It should be appreciated that the profile associated with the expected event **604** is zero except during those time trials when the expected event is active. FIG. 9 is a modified version of the graph shown in FIG. 6 showing a different illustrative computer performance **900** with two expected events **902** and **904** superimposed on the normal system behavior **906**. Expected event **902** occurs twice during the illustrated cycle while expected event **904** occurs once and is not zero only during half a period of the normal system behavior **906**. It should be appreciated that the expected event processor **52** described above augments the engine system **10** to independently estimate (i.e., impute for the current time trial and forecast for future time trials), and learn the behavior of (i.e., update the learned parameters for), the normal system behavior **906** as well as multiple expected events represented by the expected events **902** and **904** that overlap in time.

It should also be understood that the expected event scheduler **50** and processor **52** may be invoked locally or remotely, and may obtain its data locally or remotely, from one source or from several sources, and may report its output results locally or remotely, for example to a third party human or computer application. In addition, a remote invocation of the scheduled and seasonal component functions may be programmatic or via a human user interface, for example via a web browser interface or a graphical user interface. The output reporting method may also be programmatic or human readable, for example via text, web browser based or graphical reporting interface.

It should also be appreciated that a single expected event scheduler **50** and processor **52** may be used to provide analytical and reporting services for a number of engine systems, for example on a fee-for-service basis. That is, a number of engine systems deployed in distributed systems may periodically contact a single remotely-located expected event scheduler **50** and processor **52** to obtain estimation services that take the expected events into consideration. In particular, scheduled maintenance to periodically perform these operations may be scheduled to occur automatically and during convenient times, such as at night or on weekends. In addition, thin client applications, such as a browser or a browser enhanced by a JAVA download, may be used to access and control a remote scheduled and seasonal component processor and receive its reported results over a network, such as the Internet, for real-time engine system analysis. Access to this type of expected event scheduler **50** and processor **52** may be provided as a fee-for-service basis during regular business working hours. In this manner, a single expected event scheduler **50** and processor **52** may support a large number of operating engine systems, providing both scheduled maintenance and real-time engine support. Many other computer architectures and business models for deploying the expected event scheduler **50** and processor **52** will become apparent to those skilled in the art, and fall within the spirit and scope of the present invention.

CLAIMS

The invention claimed is:

1. In or for an estimation system for a host system operable for receiving input values for successive time trials and, for each time trial, computing output values based on the input values and learned parameters and updating the learned parameters to reflect relationships observed among the input and output values, a method comprising the steps of:

identifying expected events;

provisioning the estimation system with learned parameters for the expected events;

initializing the learned parameters for the expected events; and

running the estimation system to forecast operation of the host system as effected by the expected events while updating the learned parameters including the learned parameters for the expected events.

2. The method of claim 1, wherein the step of running the estimation system comprises the steps of:

(a) receiving measured data corresponding to operation of the host system for a current time trial;

(b) estimating operation of the host system for the current time trial using imputed learned parameters;

(c) predicting operation of the host system for future time trial using forecasted learned parameters;

(d) updating the learned parameters based on the measured data received for the current time trial; and

repeating the steps (a) through (d) for a number of successive time trials.

3. The method of claim 1, wherein the expected events comprise scheduled events.

4. The method of claim 1, wherein the expected events comprise seasonal events.

5. The method of claim 1, wherein the expected events comprise scheduled and seasonal events.

6. The method of claim 1, wherein:

the expected events comprise multiple overlapping expected events; and

the learned parameters including weighting factors for the overlapping expected event.

7. The method of claim 6, wherein expected events overlap in time.

8. The method of claim 7, wherein the host system is a computer system and the estimation system forecasts the performance of the computer system.

9. The method of claim 8, wherein the host system comprises a computer system comprises a computer network including application servers, storage servers, routers, and interconnecting data transmission lines.

10. The method of claim 9, wherein the expected events include end-of-month processing events and end-of-quarter processing events.

11. The method of claim 9, wherein the expected events include weekends and holidays.

12. The method of claim 9, wherein the expected events include scheduled backup events.

13. The method of claim 9, wherein the measured data comprises data received from one or more monitoring agents deployed within the computer system.

14. The method of claim 9, wherein the measured data comprises data received from one or more sources external to the computer system.

15. The method of claim 9, wherein the measured data comprises data received from one or more monitoring agents deployed within the computer system and data received from one or more sources external to the computer system.

16. In or for an computer performance estimation system operable for receiving input values for successive time trials and, for each time trial, computing output values based on the input values and learned parameters and updating the learned parameters to reflect relationships observed among the input and output values, a method comprising the steps of:

identifying expected events including scheduled events;

provisioning the estimation system with learned parameters for the expected events;

initializing the learned parameters for the expected events; and

running the estimation system to forecast performance of the computer system as effected by the scheduled events while updating the learned parameters including the learned parameters for the scheduled events.

17. The method of claim 16, wherein the step of running the computer performance estimation system comprises the steps of:

(a) receiving measured data from corresponding to operation of the computer system for a current time trial, the measured data including date received from one or more monitoring agents deployed within the computer system;

(b) estimating operation of the computer system for the current time trial using imputed learned parameters;

(c) predicting operation of the computer system for future time trial using forecasted learned parameters;

(d) updating the learned parameters based on the measured data received for the current time trial; and

repeating the steps (a) through (d) for a number of successive time trials.

17. The method of claim 16, wherein the expected events further seasonal events including weekends and holidays.

18. The method of claim 16, wherein:

the expected events comprise multiple expected events that overlap in time; and

the learned parameters including weighting factors for the overlapping expected event.

19. The method of claim 18, wherein the host system comprises a computer system comprises a computer network including application servers, storage servers, routers, and interconnecting data transmission lines.

20. The method of claim 19, wherein the expected events further include end-of-month processing events and end-of-quarter processing events.

21. In or for an computer performance estimation system operable for receiving input values for successive time trials and, for each time trial, computing output values based on the input values and learned parameters and updating the learned parameters to reflect relationships observed among the input and output values, a method comprising the steps of:

identifying expected events including scheduled events;

provisioning the estimation system with learned parameters for the expected events;

initializing the learned parameters for the expected events;

running the estimation system to forecast performance of the computer system as effected by the scheduled events while updating the learned parameters including the learned parameters for the scheduled events; and

wherein the step of running the computer performance estimation system comprises the steps of (a) receiving measured data from corresponding to operation of the computer system for a current time trial, the measured data including date received from one or more monitoring agents deployed within the computer system; (b) estimating operation of the computer system for the current time trial using imputed learned parameters; (c) predicting operation of the computer system for future time trial using forecasted learned parameters; (d) updating the learned parameters based on the measured data received for the

current time trial; and repeating the steps (a) through (d) for a number of successive time trials.

22. The method of claim 21, wherein the expected events further seasonal events including weekends and holidays.

23. The method of claim 21, wherein:

the expected events comprise multiple expected events that overlap in time; and

the learned parameters including weighting factors for the overlapping expected event.

24. The method of claim 21, wherein the host system comprises a computer system comprises a computer network including application servers, storage servers, routers, and interconnecting data transmission lines.

25. The method of claim 21, wherein the expected events further include end-of-month processing events and end-of-quarter processing events.

26. A computer-based estimation system configured to perform the steps recited in claim 1.

27. A computer storage medium storing executable instruction for causing a computer system to implement the method recited in claim 1.

28. A computer-based estimation system configured to perform the method recited in claim 16.

29. A computer storage medium storing executable instruction for causing a computer system to implement the method recited in claim 21.

30. A computer-based estimation system configured to perform the method recited in claim 16.

31. A computer storage medium storing executable instruction for causing a computer system to implement the method recited in claim 21.

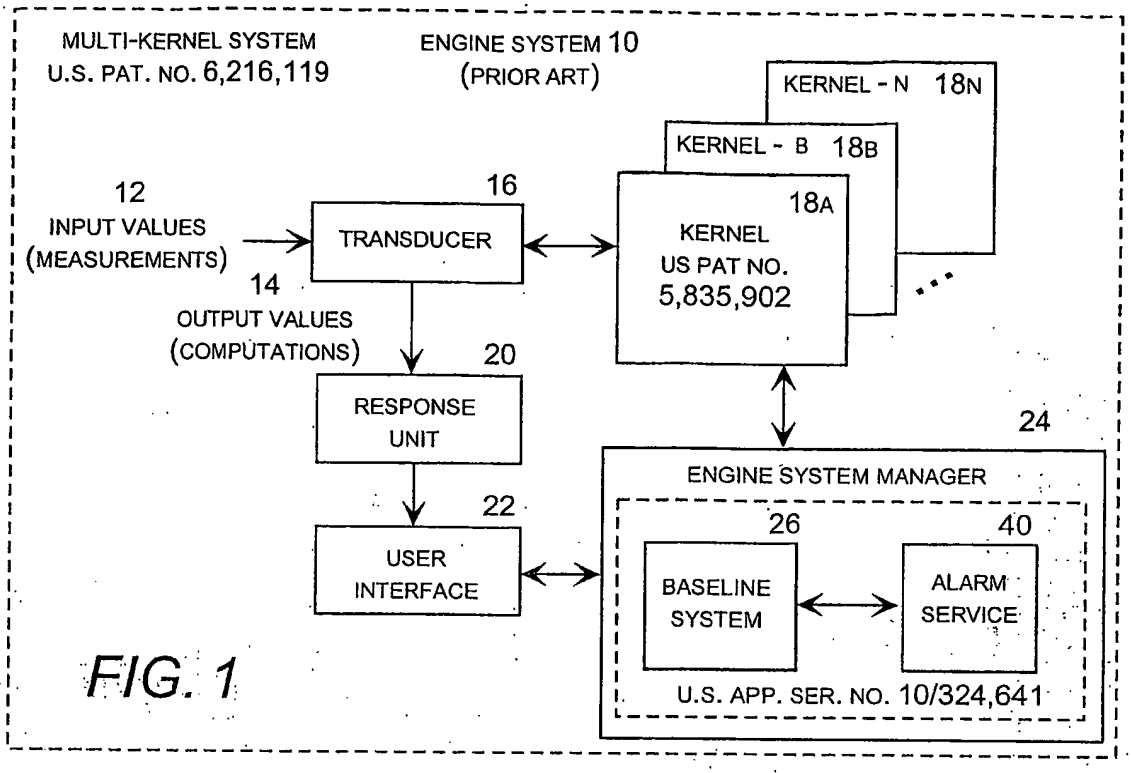
MULTI-KERNEL SYSTEM
U.S. PAT. NO. 6,216,119
ENGINE SYSTEM 10
(PRIOR ART)
KERNEL - N 18N
KERNEL - B 18B
18A
KERNEL
US PAT NO.
5,835,902
12
INPUT VALUES
(MEASUREMENTS)
16
TRANSDUCER
14
OUTPUT VALUES
(COMPUTATIONS)
20
RESPONSE
UNIT
22
USER
INTERFACE
24
ENGINE SYSTEM MANAGER
26
BASELINE
SYSTEM
40
ALARM
SERVICE
U.S. APP. SER. NO. 10/324,641

FIG. 1

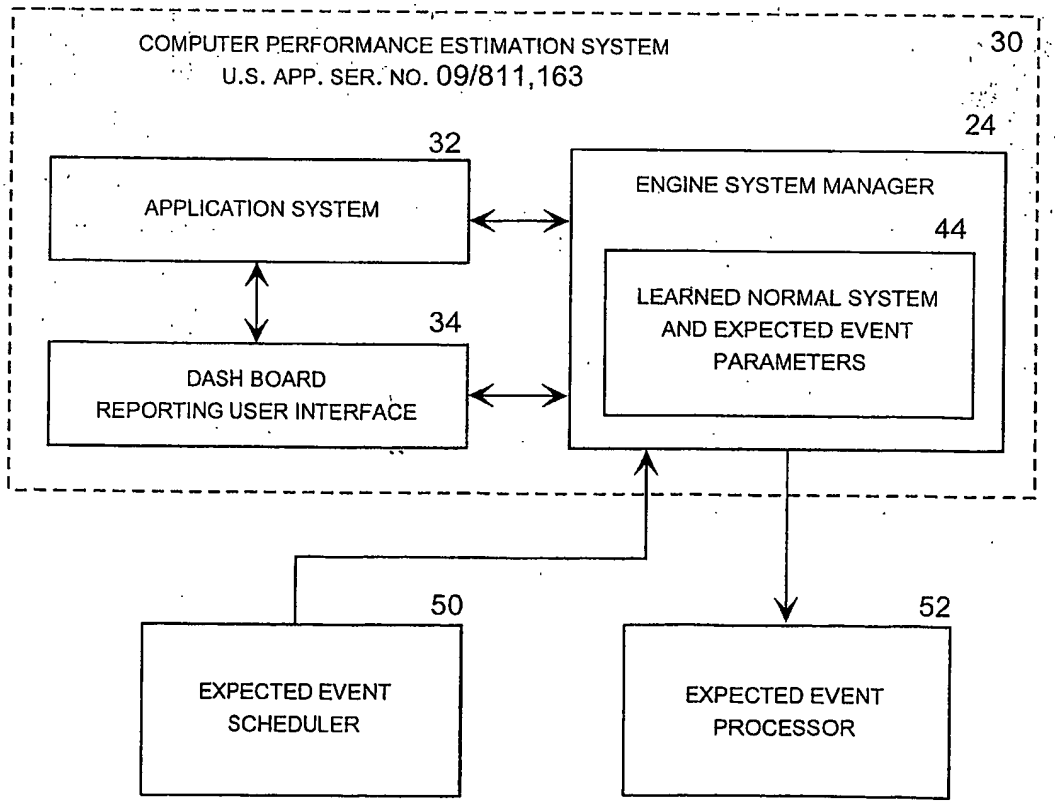
COMPUTER PERFORMANCE ESTIMATION SYSTEM
U.S. APP. SER. NO. 09/811,163
30
24
32
APPLICATION SYSTEM
ENGINE SYSTEM MANAGER
44
LEARNED NORMAL SYSTEM
AND EXPECTED EVENT
PARAMETERS
34
DASH BOARD
REPORTING USER INTERFACE
50
EXPECTED EVENT
SCHEDULER
52
EXPECTED EVENT
PROCESSOR

FIG. 2

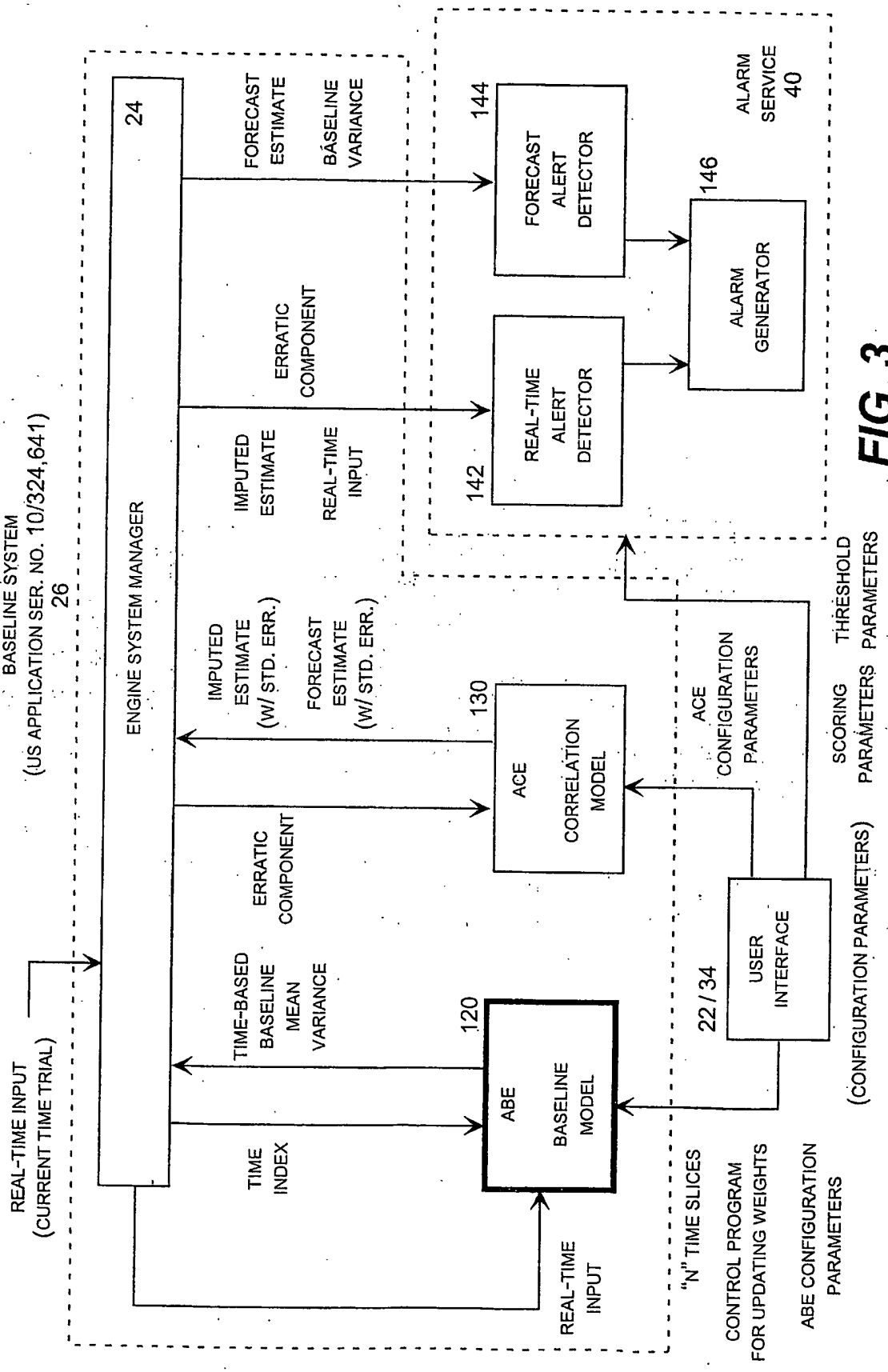
BASELINE SYSTEM
(US APPLICATION SER. NO. 10/324,641)
26
ENGINE SYSTEM MANAGER
24
REAL-TIME INPUT
(CURRENT TIME TRIAL)
TIME INDEX
TIME-BASED BASELINE MEAN VARIANCE
ERRATIC COMPONENT
IMPUTED ESTIMATE (W/ STD. ERR.)
FORECAST ESTIMATE (W/ STD. ERR.)
IMPUTED ESTIMATE
REAL-TIME INPUT
ERRATIC COMPONENT
FORECAST ESTIMATE
BASELINE VARIANCE
ABE BASELINE MODEL
120
ACE CORRELATION MODEL
130
USER INTERFACE
22 / 34
REAL-TIME ALERT DETECTOR
142
FORECAST ALERT DETECTOR
144
ALARM GENERATOR
146
ALARM SERVICE
40
REAL-TIME INPUT
"N" TIME SLICES
CONTROL PROGRAM FOR UPDATING WEIGHTS
ABE CONFIGURATION PARAMETERS
(CONFIGURATION PARAMETERS)
SCORING PARAMETERS
THRESHOLD PARAMETERS
ACE CONFIGURATION PARAMETERS

FIG. 3

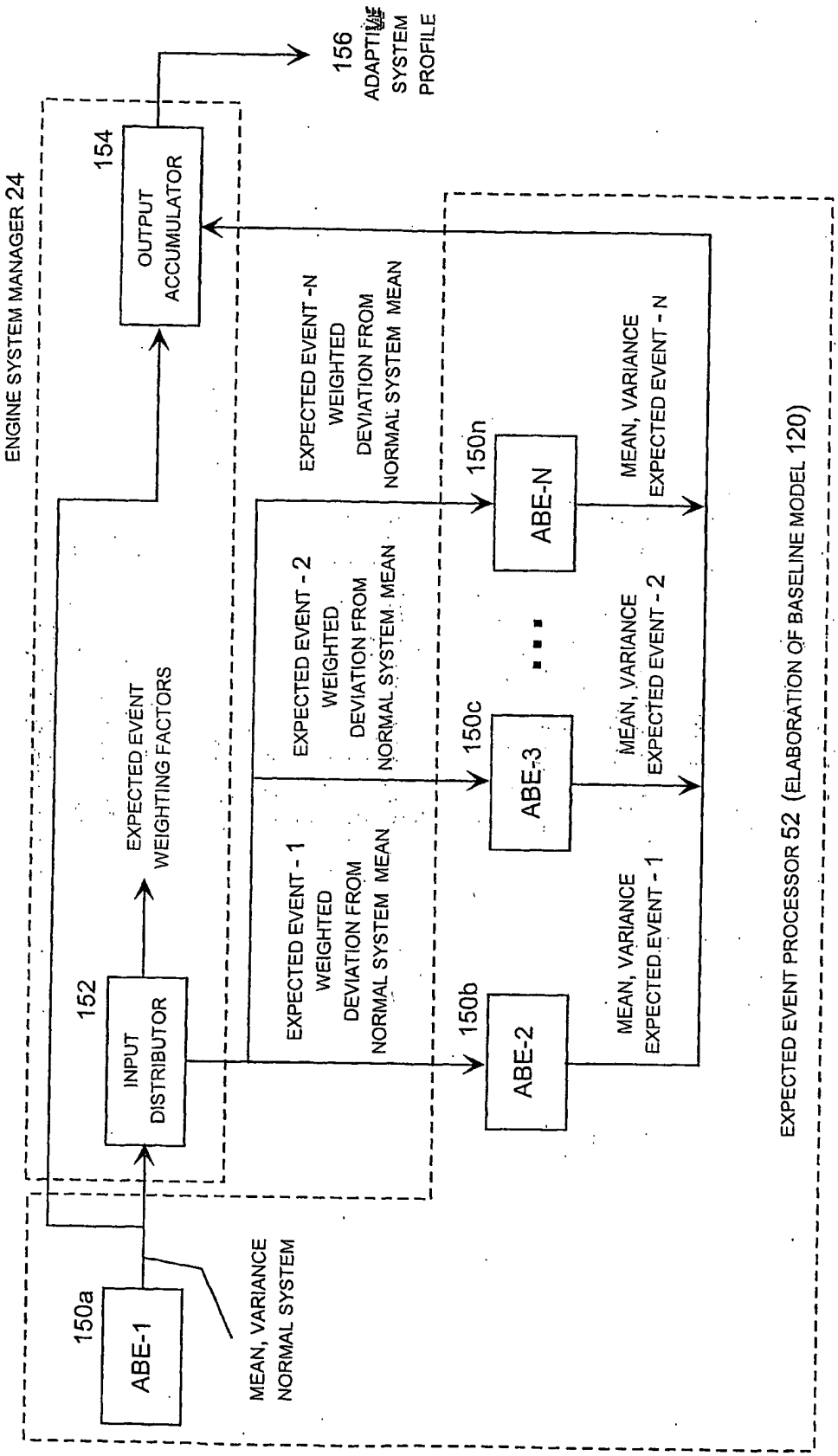
ENGINE SYSTEM MANAGER 24
EXPECTED EVENT PROCESSOR 52 (ELABORATION OF BASELINE MODEL 120)
150a
ABE-1
MEAN, VARIANCE NORMAL SYSTEM
152
INPUT DISTRIBUTOR
EXPECTED EVENT WEIGHTING FACTORS
154
OUTPUT ACCUMULATOR
156 ADAPTIVE SYSTEM PROFILE
150b
ABE-2
150c
ABE-3
150n
ABE-N
EXPECTED EVENT - 1 WEIGHTED DEVIATION FROM NORMAL SYSTEM MEAN
EXPECTED EVENT - 2 WEIGHTED DEVIATION FROM NORMAL SYSTEM MEAN
EXPECTED EVENT -N WEIGHTED DEVIATION FROM NORMAL SYSTEM MEAN
MEAN, VARIANCE EXPECTED EVENT - 1
MEAN, VARIANCE EXPECTED EVENT - 2
MEAN, VARIANCE EXPECTED EVENT - N

FIG. 4

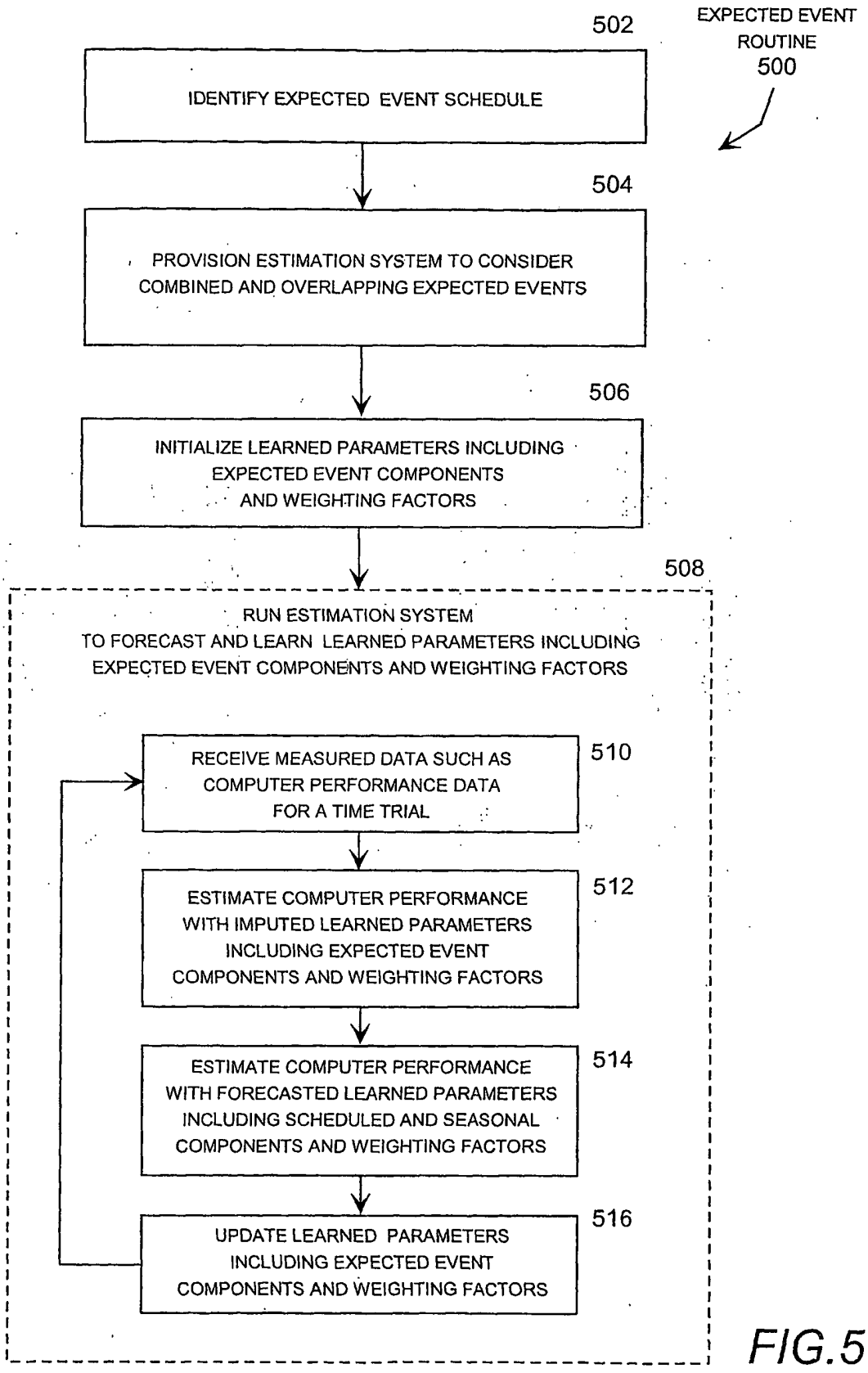
EXPECTED EVENT ROUTINE
500
502
IDENTIFY EXPECTED EVENT SCHEDULE
504
PROVISION ESTIMATION SYSTEM TO CONSIDER COMBINED AND OVERLAPPING EXPECTED EVENTS
506
INITIALIZE LEARNED PARAMETERS INCLUDING EXPECTED EVENT COMPONENTS AND WEIGHTING FACTORS
508
RUN ESTIMATION SYSTEM TO FORECAST AND LEARN LEARNED PARAMETERS INCLUDING EXPECTED EVENT COMPONENTS AND WEIGHTING FACTORS
510
RECEIVE MEASURED DATA SUCH AS COMPUTER PERFORMANCE DATA FOR A TIME TRIAL
512
ESTIMATE COMPUTER PERFORMANCE WITH IMPUTED LEARNED PARAMETERS INCLUDING EXPECTED EVENT COMPONENTS AND WEIGHTING FACTORS
514
ESTIMATE COMPUTER PERFORMANCE WITH FORECASTED LEARNED PARAMETERS INCLUDING SCHEDULED AND SEASONAL COMPONENTS AND WEIGHTING FACTORS
516
UPDATE LEARNED PARAMETERS INCLUDING EXPECTED EVENT COMPONENTS AND WEIGHTING FACTORS

FIG.5

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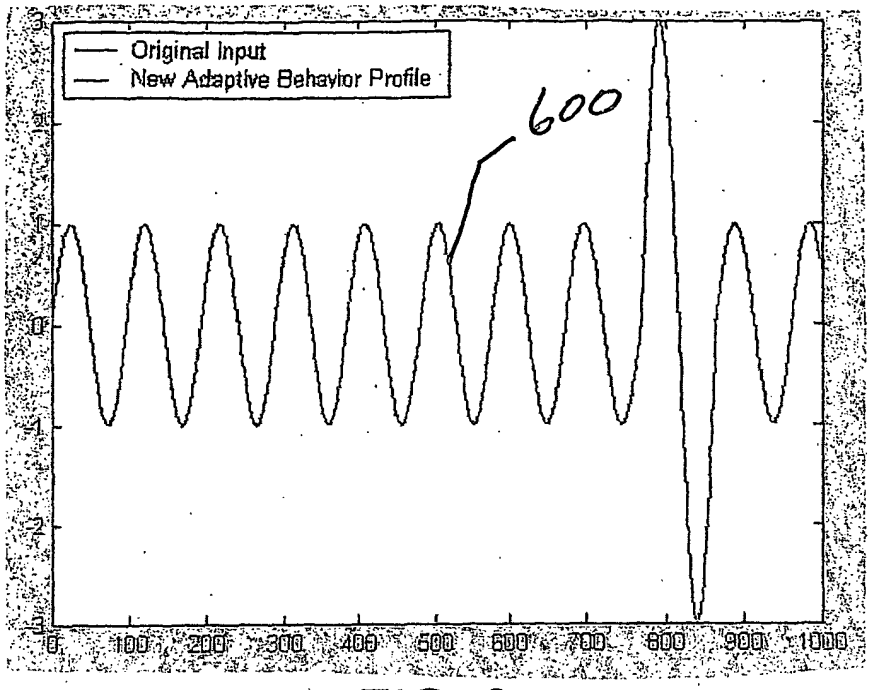

FIG. 6

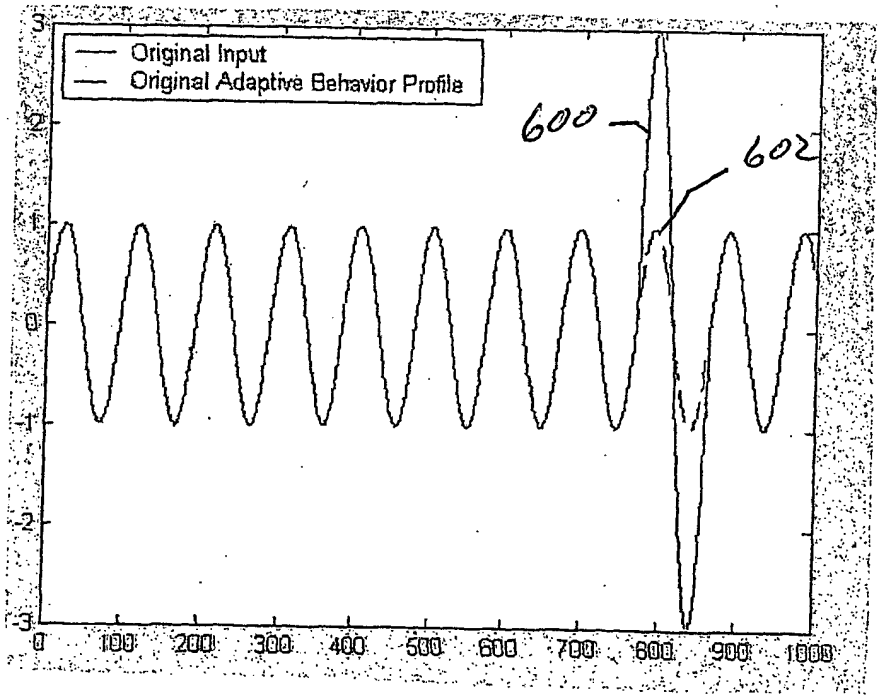

FIG. 7

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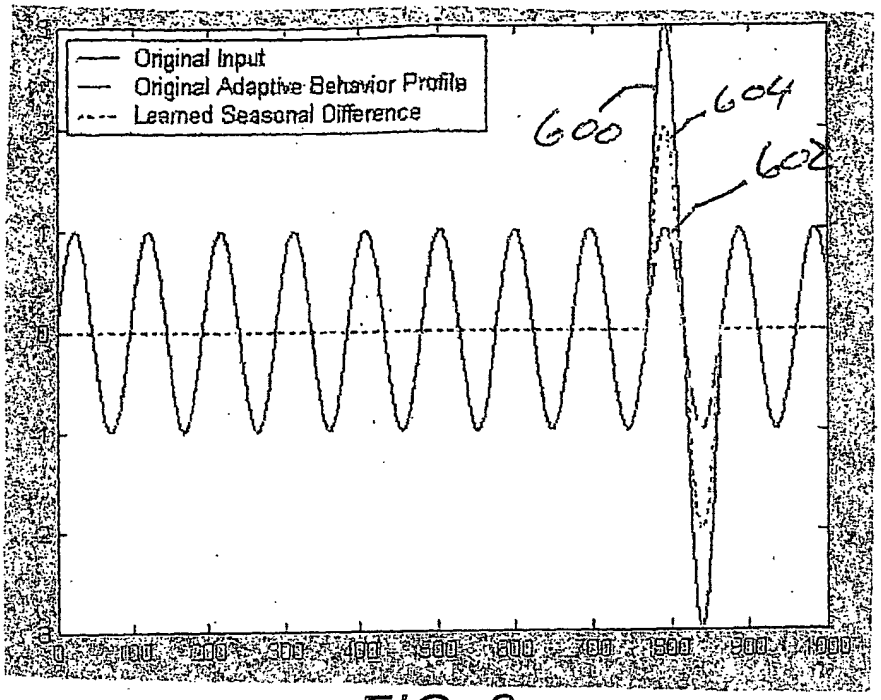

FIG. 8

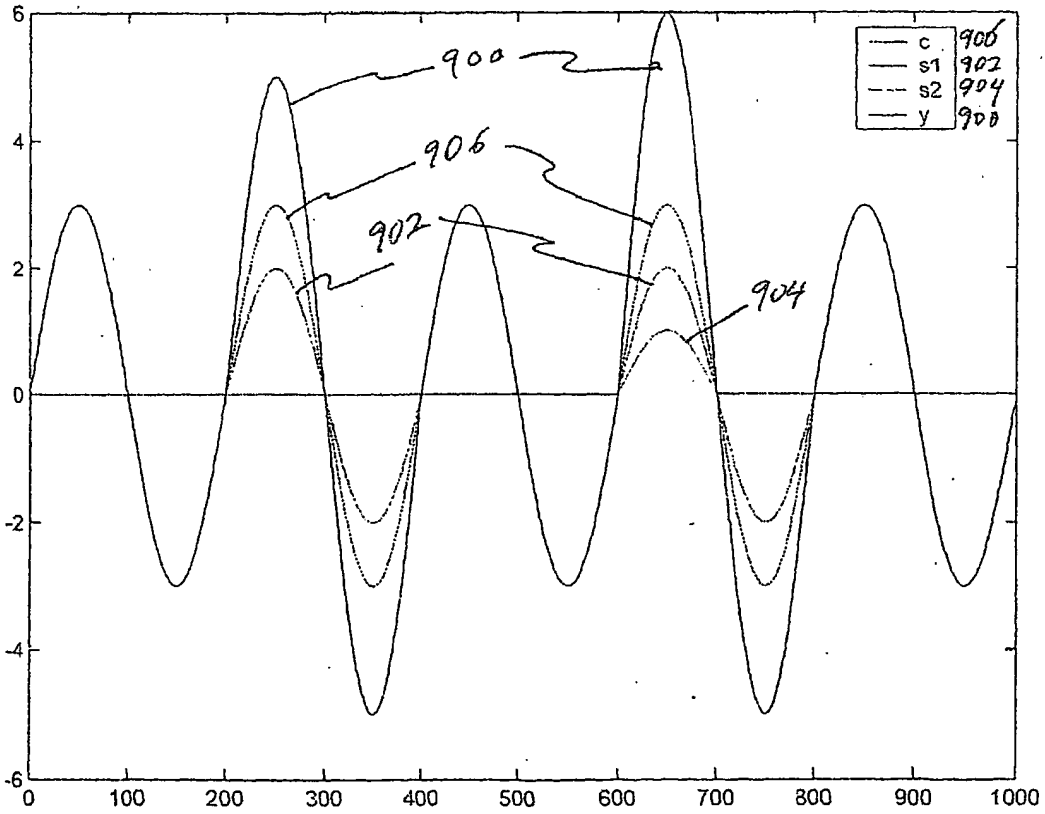

FIG. 9